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A RECOGNITION OF ECG ARRHYTHMIAS USING ARTIFICIAL NEURAL NETWORKS

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Abstract – **In this study, Artificial Neural Networks (ANN) has been used to classify the ECG arrhythmias. Types of arrhythmias chosen from MIT-BIH ECG database to train ANN include normal sinus rhythm, sinus bradycardia, ventricular tachycardia, sinus arrhythmia, atrial premature contraction, paced beat, right bundle branch block, left bundle branch block, atrial fibrillation, and atrial flutter have been as. The different structures of ANN have been trained by arrhythmia separately and also by mixing these 10 different arrhythmias. The most appropriate ANN structure is used for each class to test patients' records. The ECG records of 17 patients whose average age is 38.6 were made in the Cardiology Department, Faculty of Medicine at Selçuk University. Forty-two different test patterns were extracted from these records. These patterns were tested with the most appropriate ANN structures of single classification case and mixed classification cases. The average error of single classifications was found to be 4.3% and the average error of mixed classification 2.2%.**

Keywords– Arrhythmia classification, artificial neural networks, ECG, heart diseases

I. INTRODUCTION

Heart diseases, which are one of the death reasons of man/women, are among the important problems on this century. Early diagnosis and medical treatment of heart diseases can prevent sudden death of the patient. One of the ways to diagnose heart diseases is to use electrocardiogram (ECG) signals. ECG signals are formed of P wave, QRS complex, and T wave. They are designated by capital letters P, Q, R, S, and T. In the normal beat phase of a heart, the main parameters, inspected include the shape, the duration, and the relationship with each other of P wave, QRS complex, and T wave components and R-R interval. The changes in these parameters indicate an illness of the heart that may occur by any reason. All of the irregular beat phases are generally called arrhythmia and some arrhythmias are very dangerous for patient. Some automatic ECG interpreting systems is available. Moreover, the computer-based interpreter systems are currently being developed to diagnose arrhythmia in time, and various methods are applied to these systems with one of them being Artificial Neural Networks (ANN).

The art of ECG interpretation is basically recognition of a pattern. To date, several researchers have made attempts to use ANN to classify electrocardiograph beats. Suzuki [1] developed a system called "self-organising QRS-wave recognition in ECG using neural networks", and used ART (Adaptive Resonance Theory) on his study. Devine and Macfarlane [2] investigated the use of ANN for the classification of ST-T abnormalities of the ECG. Yeap et al. [3] proposed to use the amplitude of the QRS, the offset of QRS, the T-wave slope, and the prematurely as the inputs to an ANN structure with 20 hidden units. Linnenbank et al. [4] used a three-layer ANN model to classify 62-lead ventricular tachycardia QRS integral map patterns. Tsai et al. [5] used power spectral density of the electrocardiograph signals as input to classify five different types of normal and abnormal electrocardiograph beats. Lee [6] reported the use of a higher-order ANN model for electrocardiograph classification.

Hu et al. [7] investigated potential applications of ANN for QRS detection and beat classification. They used an adaptive multilayer perceptron structure to model the non-linear background noise so as to enhance the QRS complexities. This provided more reliable detection of QRS complexities even in a noisy environment. Bortalan and Willems [8] illustrated the use of ANN approach for the problem of diagnostic classification of resting 12-lead ECG with seven diagnostic classes: normal, left, right, and biventricular hypertrophy, and anterior, inferior, and combined myocardial infarction. Edenbrandt et al. [9] proved that the use of the ANN for the diagnosis of myocardial infarction (MI) and ventricular hypertrophy, and the classification of ST-T segments were useful. Dassen et al. [10] used the ANN and Brugada criteria for the supraventricular tachycardia (SVT) and ventricular tachycardia (VT) diseases. Clayton et al. [11] studied the recognition of ventricular fibrillation (VF) using ANN. Karlik and Derelioðlu [12] classified 11 different arrhythmias by simulating according to R peaks, using ANN. Ham and Han [13] investigated the QRS complex, extracted from ECG data, using arrhythmias. Özbay et al. [14] classified right and left bundle branch block using ANN. Silipo et al. [15] compared in a subtle ECG classification task using two classification techniques one with supervised and the other with unsupervised learning.

In this study, using two different architectures of multi-layered neural networks, we performed waveform detection. These networks were comparatively examined to detect 10 different ECG waveforms.

II. METHODOLOGY

In this study, the back-propagation learning algorithm is used since it is the most popular supervised learning algorithm [16]. To test the patient records using ANN

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structures software called ECGWin was developed. The software is easy to use since it was developed by Windows programming tools.

1) Teaching ECG Arrhythmias to the ANN

Types of arrhythmias selected from MIT-BIH database [17] to train ANN include normal sinus rhythm, sinus bradycardia, ventricular tachycardia, sinus arrhythmia, atrial premature contraction, paced beat, right bundle branch block, left bundle branch block, atrial fibrillation and atrial flutter. All data used were filtered, R peaks found, and patterns normalised between 0-1. Both patterns, used in training of ANN, and obtained from patients' records were arrenged as 200 samples in the intervals of R-R, and each of them were called as a set. So, all these sets fed inputs of ANN in sequence.

A. Training the ANN according to single arrhythmia type

Different structures of ANN were trained using these ten different arrhythmias separately. There were arrhythmia used data and normal data in the pattern. If the value of node output of output layer was logic-1, we interpreted this as arrhythmia. If the value was logic-0, this was considered as normal. If $y(i) \geq 0.5$, we accept as logic-1 and we used $h(i)=|1-y(i)|$ in the error calculation. If $y(i)<0.5$, it was considered as logic-0 and we used $h(i)=|0-y(i)|$. Trained ANN architectures were 200:3:1, $\varepsilon=1$ (learning rate), and $\alpha=0.5$ (momentum coefficient) for 10 different arrhythmias.

B. Training the ANN according to mixing classification

Normal sinus rhythm, sinus bradycardia, ventricular tachycardia, sinus arrhythmia, atrial premature contraction, paced beat, right bundle branch block, left bundle branch block, atrial fibrillation, and atrial flutter were mixed in sequence. The length of the training pattern was 21200 samples (106 sets). The test pattern was done similarly. Both patterns, used in training of ANN, and used in testing trained ANN were occured from MIT-BIH ECG database. Nodes of the output layer of the ANN were Q_1=N, Q_2=Br, Q_3=VT, Q_4=SA, Q_5 =APC, Q_6=P, Q_7=R, Q_8=L, Q_9=A.Fib., and Q_{10}=A.Fl. Architecture of the trained ANN was 200:15:10 as seen in Figure-1. Learning rate (ε) was 1 and momentum coefficient (α) was 0.2. Whereas training error was found 0.1% after 10000 iteration, test error became 1.3%. Change of error by iteration is seen in Figure 2.

We developed an algorithm for evaluation of test results in the mixed classification. Desired values of node outputs of the output layer were logic-1 or logic-0 in the training pattern. Node outputs were changing between 0-1. If one of the node outputs of the output layer, $y(i) \geq 0.5$ and $y(i)>$(other node outputs), we interpreted this as arrhythmia for the corresponding node, and we used $h(i)=|1-y(i)|$ in the error calculation. If $y(i)<0.5$ we interpreted it as normal, and we used $h(i)=|0-y(i)|$. If all of node outputs were $y(i)<0.5$, then an unknown state occurs. ANN did not classify this test pattern since similar pattern was not taught to the ANN beforehand.

2) ECG recordings

Figure 3 shows the system used in this study for recordings of ECG signals [18]. Derivation II or V5 was chosen and Ag-AgCl was used as surface electrodes. Outside ECG device was amplified and filtered by Low Pass Filter that was second order Butterworth and has cut-off frequency of 28 Hz. Then, we added dc level on the filtered signal in order to have accord with I/O card. Finally, we recorded the ECG signals of patients on PC; sampling frequency was 360 Hz.

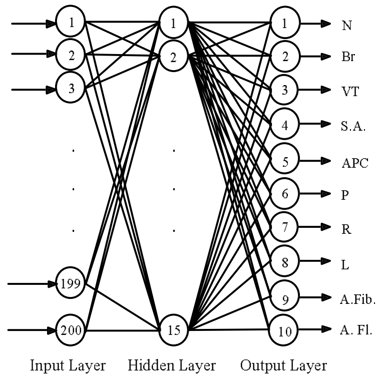

Fig.1. Architecture of the ANN in the mixed classification

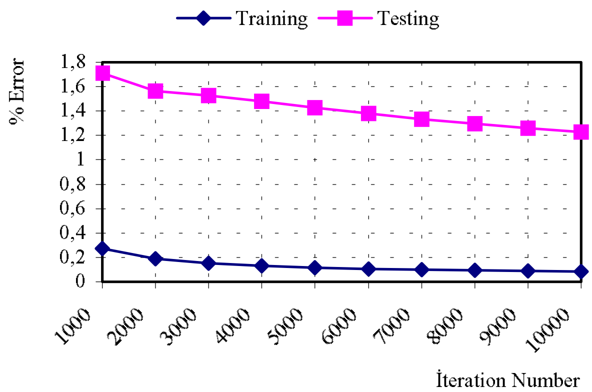

Fig. 2 . Variation of errors in respect of iteration number for training and testing

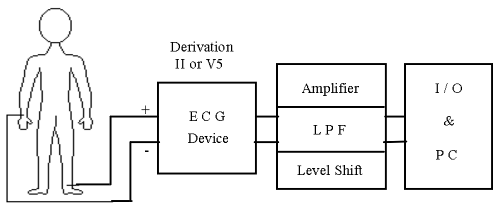

Fig. 3. ECG recording system

3) The ECGWin Software

Software referred to, as ECGWin was developed to evaluate and monitor the ECG records of patients. Figure 4 shows the used interface of the software program was developed by Delphi high level programming language. The ECGWin Software includes real-time monitoring and recording, filtering, finding the R peaks, artificial neural networks, displaying outputs, drawing, and storing patient information.

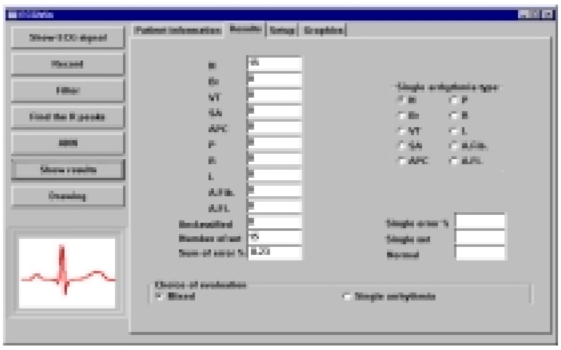

Fig. 4. The ECGWin Software

III. RESULTS

The ECG records of 17 patients, with an average age of 38.6, were obtained in the Cardiology Department of Medical Faculty of Selcuk University, Konya, Turkey. Forty-two test patterns in different lengths were formed with these records. These test patterns were filtered, and normalised between 0-1. Obtained from patients' records were arrenged as 200 samples in the intervals of R-R. Then, these patterns were tested with the most appropriate ANN structures of single classification cases and mixed classification case. As a result of the test, the average error of single classifications was obtained 4.3% and has mixed classification 2.2%, as shown in Table 1. The results of patients' records in mixed classification are shown in Table 2.

IV. DISCUSSION

Our target was to detect a lot of ECG signals and to recognise ECG arrhythmias. In this study in which ANN was employed as the basic method accuracy rates were appeared better than similar studies. Moreover, number of arrhythmias can be increased in the ECGWin Software. Therefore, lots of patients' ECGs can be investigated and interpreted in a very short time. This will improve the performance of heart treatment. These studies divided two major groups, in terms of the data used. Those using MIT-BIH ECG arrhythmia database and those is using other data. It can easily be observed that our study is more recognised than other studies using MIT-BIH database. Moreover we used data obtained from patients together with MIT-BIH data.

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TABLE 2. Test results of the patterns of patients' ECGs

Arrhythmia classification types	ANN architectures	ε	α	number of patients	number of patterns	number of sum sets	Average Error %	Classification accuracy %
Normal sinus rhythm	200:3:1	1	0.5	17	42	3203	0.1	99.9
Sinus bradycardia	200:3:1	1	0.5	17	42	3203	5.6	94.4
Ventricular tachycardia	200:3:1	1	0.5	17	42	3203	5.4	94.6
Sinus arrhythmia	200:3:1	1	0.5	17	42	3203	2.9	97.1
Atrial premature contrac.	200:3:1	1	0.5	17	42	3203	4.3	95.7
Paced beat	200:3:1	1	0.5	17	42	3203	5	95
Right bundle branch bloc	200:3:1	1	0.5	17	42	3203	5.3	94.7
Left bundle branch block	200:3:1	1	0.5	17	42	3203	6.3	93.7
Atrial fibrillation	200:3:1	1	0.5	17	42	3203	2.2	97.8
Atrial flutter	200:3:1	1	0.5	17	42	3203	6.3	93.7
							average:4.3	average:95.7
Mixed classification	200:15:10	1	0.2	17	42	3203	2.2	97.8

TABLE 2. Results of patients' records in mixed classification

	name	M/F	age	Number of samples	number of sets	Q_1 N	Q_2 Br	Q_3 T	Q_4 S	Q_5 Apc	Q_6 P	Q_7 R	Q_8 L	Q_9 Afib	Q_{10} Aflt	?	Error %
1-a	S.C	M	24	15000	75	75	0	0	0	0	0	0	0	0	0	0	1.1
1-b	S.C	M	24	12600	63	61	0	0	2	0	0	0	0	0	0	0	1.0
2-a	E.D	M	27	18000	90	71	0	0	18	0	0	0	0	0	0	1	2.5
2-b	E.D	M	27	14800	74	15	3	0	41	0	0	0	0	1	0	14	2.9
3	N.Y	M	22	21000	105	0	38	0	65	0	0	0	0	0	0	2	2.0
4	Ö.A	M	24	17400	87	54	0	0	32	0	0	0	0	0	0	1	1.3
5-a	Y.E	M	33	17600	88	2	15	0	67	0	0	0	0	0	0	4	4.2
5-b	Y.E	M	33	9800	49	0	7	0	40	0	0	0	0	0	0	2	3.8
6-a	M.Ý	M	27	8600	43	43	0	0	0	0	0	0	0	0	0	0	0.1
6-b	M.Ý	M	27	17800	89	62	1	0	25	0	0	0	0	0	0	1	1.0
7-a	D.C	M	23	11200	56	35	0	0	10	0	0	0	0	0	0	11	3.0
7-b	D.C	M	23	3600	18	0	18	0	0	0	0	0	0	0	0	0	3.4
7-c	D.C	M	23	18600	93	51	18	0	3	0	0	0	0	0	0	21	3.7
8-a	R.K	M	24	11600	58	0	10	0	42	0	0	0	0	0	0	6	2.1
8-b	R.K	M	24	12200	61	0	2	0	56	0	0	0	0	0	0	3	1.9
8-c	R.K	M	24	13600	68	0	8	0	44	0	0	0	0	0	0	16	2.7
9-a	S.Ö	F	24	13600	68	0	0	0	68	0	0	0	0	0	0	0	1.4
9-b	S.Ö	F	24	18200	91	0	0	0	91	0	0	0	0	0	0	0	1.5
9-c	S.Ö	F	24	13800	69	0	6	0	63	0	0	0	0	0	0	0	2.2
9-d	S.Ö	F	24	15600	78	0	0	0	78	0	0	0	0	0	0	0	1.5
10-a	Y.Ö	M	32	16800	84	40	0	0	18	0	0	0	0	3	0	23	2.7
10-b	Y.Ö	M	32	19400	97	96	0	0	0	0	0	0	0	0	0	1	0.3
11-a	D.A	M	63	17400	87	0	0	1	0	0	0	86	0	0	0	0	2.7
11-b	D.A	M	63	15200	76	0	0	0	0	0	0	76	0	0	0	0	2.9
12-a	E.S	F	55	17200	86	0	22	0	0	0	0	0	0	0	0	64	0.9
12-b	E.S	F	55	20000	100	0	38	0	4	0	0	34	0	0	0	24	5.8
13-a	G.Y	F	65	10000	50	0	0	0	1	0	0	0	0	41	2	6	1.8
13-b	G.Y	F	65	19600	98	0	3	0	6	0	0	0	0	75	3	11	2.5
13-c	G.Y	F	65	18000	90	0	17	0	6	0	0	0	0	60	1	6	1.7
14-a	O.U	M	51	9200	46	0	0	29	0	0	0	0	0	0	0	17	2.0
14-b	O.U	M	51	16000	80	0	7	19	30	0	0	19	0	0	0	5	1.3
14-c	O.U	M	51	10000	50	0	2	8	0	0	0	40	0	0	0	0	0.9
15-a	S.A	F	80	20000	100	0	0	1	0	0	0	99	0	0	0	0	1.0
15-b	S.A	F	80	15600	78	0	0	1	0	0	0	78	0	0	0	0	0.2
15-c	S.A	F	80	19000	95	0	0	0	0	0	0	82	0	0	0	13	1.1
16-a	S.G	F	66	14600	73	0	0	0	2	0	0	0	0	65	0	6	3.3
16-b	S.G	F	66	14200	71	0	0	0	35	0	0	0	0	30	0	6	2.6
16-c	S.G	F	66	20800	104	0	0	0	103	0	0	0	0	0	0	1	1.6
17-a	Z.E	F	16	12200	61	1	0	0	1	0	0	0	0	3	0	56	3.0
17-b	Z.E	F	16	16800	84	0	0	0	14	0	0	0	0	2	0	68	2.6
17-c	Z.E	F	16	16000	80	3	0	0	36	0	0	0	0	0	0	41	3.0
17-d	Z.E	F	16	18000	90	0	0	0	0	0	0	90	0	0	0	0	4.8

Mean = 2.2